Research on Alternative Fuel Vehicle Fluctuation Based on GARCH-MIDAS Model

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Abstract. This article uses the GARCH-MIDAS model to analyze the impact of economic uncertainty on the volatility of the new energy vehicle market. Economic uncertainty includes economic policy uncertainty and macroeconomic uncertainty. Use EPU as the proxy variable for economic policy uncertainty, and the Manufacturing Purchasing Managers Index (PMI) as the proxy variable for macroeconomic uncertainty. The results indicate that economic policy uncertainty has a significant negative impact on the volatility of the new energy vehicle market. The PMI index's impact weight on the new energy vehicle sector has slowly decreased over the past 12 months, indicating that the macroeconomic indicators of the manufacturing industry have a relatively long impact on the new energy vehicle sector, which takes about a year to dissipate, The fluctuation of economic policy uncertainty on the new energy vehicle market is transmitted through the EPU index, and the impact of economic policy uncertainty presents a short-term effect. Policy shocks are absorbed within 2 months and will not have a long-term impact on the stock market. Among all economic uncertainty factors, economic operation has the most significant impact on long-term volatility. Overall, macroeconomic uncertainty does not have a significant impact on the volatility of the new energy vehicle market, and its contribution is limited.

Keywords: Stock price volatility of Alternative fuel vehicle; Macroeconomic uncertainty; Economic policy uncertainty; GARCH-MIDAS.

1. Introduction

Realizing carbon peak and carbon neutrality will accelerate the transformation of China's automobile industry development mode, form a "reverse force" mechanism for transformation and upgrading, accelerate the pace of reducing carbon emissions and supporting the use of renewable energy in the entire automobile industry chain system, achieve the transformation and upgrading of upstream and downstream industry chains and green and low-carbon development, and lay a more solid foundation for the transformation and upgrading of the automobile industry and green and low-carbon development, Especially in promoting the development of new industries, formats, and models represented by new energy vehicles, it has created new historical opportunities for China's automotive industry to achieve the goal of catching up and leading the way, enhancing the international competitiveness of the automotive industry. Under the dual carbon target, stable and heavy bottom chips have been added for the sustainable and high growth of the new energy industry. In 2022, the export of new energy vehicles reached 679000 units, a year-on-year increase of 120%. Since the industry giant Tesla took the lead in launching a new energy vehicle price war, domestic new energy vehicle companies have lowered prices one after another.

In addition to government reasons, this also indicates that low-carbon transformation is a major trend in industry development. This article focuses on the current dual carbon policy goal of new energy vehicles as the leading target of the automotive industry, and analyzes and studies the volatility of the new energy sector based on the GARCH-MEDIAS model.

2. Literature References

It is the cash flow of the enterprise and the required necessary rate of return that affect the fluctuation of stock price. From the perspective of the CAPM model, the necessary rate of return is not only affected by the enterprise itself, but also by Systematic risk, that is, the fluctuation of stock price is complicated by economic policy, inflation rate, market interest rate, legal changes and other factors. When observing volatility from two dimensions: long-term trend and short-term volatility, Zheng Tingguo and Shang Yuhuang's research shows that the long-term trend in volatility is influenced by the operation of the real economy (such as economic growth rate, inflation rate, etc.), financial policies (such as monetary policy, regulatory system), and market structure (such as investor composition), while short-term volatility exhibits the characteristic of mean regression, which affects policy news in the market Sudden events are more sensitive, such as regulatory measures introduced by the stock market and the tightening of market liquidity, which can cause significant fluctuations in the stock market in the short term. Xia Ting and Wen Yuechun [2] analyzed that economic uncertainty is influenced by economic policy uncertainty, economic operation, and uncertainty in consumption. Rodrik et al. [3] studied the impact of market uncertainty on corporate investment, and the results showed that an increase in uncertainty would lead to a lag in corporate investment and increase corporate costs.

Many scholars have studied ARCH models. Engle first established the autoregressive conditional Homoscedasticity and heteroscedasticity (ARCH) model to describe the "volatility aggregation" and "peak fat tail" characteristics of time series. Bollerslev proposed the GARCH model based on the ARC model, which can eliminate the GARCH effect and improve the fitting effect of the model.

Based on the GARCH-MEDIAS model proposed by Engle et al. [4], this article analyzes the impact of economic uncertainty on the volatility of returns in the current new energy vehicle market, and studies the long-term trends in stock market volatility and the response of short-term components to economic uncertainty. At the same time, a GARCH (1,1) model is established to predict stock price volatility in the new energy vehicle market.

3. Model introduction and variable selection

3.1. Model Introduction

(1) GARCH

The GARCH model, also known as the generalized autoregressive model, is an extension of the ARCH model. The GARCH (p, 0) model is equivalent to the ARCH (p) model.

$$x_t=\beta_0+\beta_1 x_{t-1}+\beta_2 x_{t-2}+\cdots+\beta_p x_{t-p}+u_t \tag{1}$$

$$\sigma_t^2=\alpha_0+\lambda_1\sigma_{t-1}^2+\cdots+\lambda_p\sigma_{t-p}^2+\alpha_1 u_{t-1}^2+\cdots+\alpha_q u_{t-q}^2 \tag{2}$$

Among them, (1) is the conditional mean equation, and (2) is the conditional variance equation, indicating the characteristics of changes in the time series. In addition, both equations simultaneously satisfy:

$$\alpha_0>0,$$
$$\alpha_i\geq 0, i=1,2,\ldots q,$$
$$\lambda_i\geq 0, i=1,2,\ldots p$$
$$\mathbf{0}\leq\left(\sum_{i=1}^{q}\alpha_i+\sum_{i=1}^{p}\lambda_i\right)<\mathbf{1}$$

Research has shown that the distribution of returns not only exhibits the characteristics of peaks and thick tails, but also exhibits asymmetric effects. When the market experiences a negative impact, the stock price drops, the conditional variance of returns increases, and the volatility of stock price and return increases. When the market experiences a positive impact, the stock price rises, but the increase is not as significant as the decrease in stock price caused by a negative impact. In the GARCH model, the impact of positive and negative shocks on the conditional variance is symmetric, so the model cannot describe the asymmetry of the conditional variance of stock returns. And the highly influential paper published by Ghysels et al. [5] indicates that GARCH family models are strictly limited by data frequency, and these models are not suitable for exploring the volatility of long-term capital markets.

(2) GARCH-MEDIAS

When matching economic information and stock market volatility, considering that the traditional same frequency Data modeling method will lose useful information of high-frequency data and avoid the bias of parameter estimation caused by model design, this paper uses the GARCH-MEDIAS model considering exogenous variables to analyze the impact of economic uncertainty on the volatility of new energy vehicle market returns. The setting of yield and volatility is as follows:

$$r_{it} = \mu_t + \sqrt{\tau_t g_{ii} \varepsilon_t}, \varepsilon_t \mid \Phi_{i-1,t} \sim N(0,1)$$
$$\sigma_{it}^2 = \tau_t g_{i,t}$$

Among them, it is the information set of the yield on the i-1st day of month t, and the volatility is influenced by long-term trends and short-term volatility. The short-term volatility follows the GARCH (1,1) model, namely:

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{\left(r_{i-1,t} - \mu\right)^2}{\tau_t} + \beta g_{i-1,t}$$

Among them, α＞ 0, β≥ 0, α＋β＜ 1. The long-term trend u is influenced by the uncertainty indicator X, and its specific form is:

$$\tau_t = m + \theta_1 \sum_{k=1}^{n} \phi_{1k}\,(\omega_{11}, \omega_{12}) X1_{t-k} + \theta_2 \sum_{k=1}^{K} \phi_{2k}\,(\omega_{21}, \omega_{22}) X2_{t-k}$$

Among them, K is the maximum lagging order and coefficient of the low-frequency variable θ_1、$\theta_2$are respectivelx_1 and x_2 The long-term impact coefficient of volatility. $\emptyset_k(\omega_1, \omega_2)$is the weight function of a beta type lagged variable, in the form of:

$$\varphi_k(\omega_1, \omega_2) = \frac{(k/K)^{\omega_1 - 1}(1 - k/K)^{\alpha_2 - 1}}{\sum_{j=1}^{K} (j/K)^{\omega_1 - 1}\,(1 - j/K)^{\omega_2 - 1}}$$

In order to ensure that the weight of the lagged variable is attenuated (the closer it is to the current period, the greater its impact on the current period), it is generally fixed ω_{11}=ω_{21} = 1 , determined by coefficientω_{12}, ω_{22}The decay rate that determines the degree of influence of low-frequency data on high-frequency data. At this point, the Beta weight function is simplified as:

$$\varphi_k(\omega_2) = \frac{((1 - k/K)^{\omega_2 - 1}}{\sum_{j=1}^{K} ((1 - j/K)^{\omega_2 - 1}}$$

When estimating the maximum lag order K in the weight function, this article uses information from the past year to estimate the fitting effect of the weight coefficient. If it is daily and monthly data, K=36; If it is daily and quarterly data, K=12. This article selects daily new energy vehicle stock market returns and monthly economic uncertainty indicator data, so K=12.

According to the distribution function and model setting of the return rate, the required parameters are obtained by maximum likelihood estimation. The maximum Likelihood function is:

$$LLF = -\frac{1}{2} \sum_{t=1}^{T} \left[log\ g_t\,(\Phi) \tau_t(\Phi) + \frac{(r_t - \mu)^2}{g_t(\Phi) \tau_t(\Phi)} \right]$$

3.2. Variables and data

This article selects the return rate of stocks in the Chinese new energy vehicle market for research. The sample period is from August 31, 2017 to August 31, 2021, with a total of 974 sets of daily return rate data.

The variables used to measure economic uncertainty are divided into two categories, namely macroeconomic uncertainty and economic policy uncertainty. These indicators are monthly data, corresponding to the sample period from August 31, 2017 to August 31, 2021, with a total of 49 sets of monthly data.

There are many factors that affect stock market volatility, which are generally divided into three categories: the operational status of the real economy, consumption status, and monetary policy. This article selects the Purchasing Managers' Index (PMI) as the explanatory variable for macroeconomic uncertainty, which is used to reflect the operational status of the real economy. Andersen et al. [6] used the industrial growth rate indicator to measure the operational status of the real economy. Compared to the industrial growth rate as a measure of the operational status of the real economy, relevant studies have shown that the lag of the response of the purchasing managers' index to the degree of economic development is shorter. Therefore, this article uses this index.

Economic policy uncertainty is measured using EPU, following the method proposed by Baker et al. [7]. Stanford University and the University of Chicago jointly released the EPU index to measure the economic policy uncertainty of a country or region.

4. Empirical analysis

4.1. Descriptive statistics

(1) Unit Root Test

This article analyzes a total of 974 daily closing price data of the "National Securities New Energy Vehicle Index" sector (399417) from September 1, 2017 to August 31, 2021, representing the corporate environment of the new energy vehicle sector.

In this paper, the Root of unity test (ADF) is used to test the stationarity of the original sequence, and the results lag 5 orders are shown in the table:

Table 1 Unit Root Test

	ADF statistics	1% critical value	5% critical value	10% critical value	P value
Drate	-30.71985	-3.436857	-2.864320	-2.568293	0.0000

The result of testing the original sequence is P-value=0<0.05, therefore it is considered that the first-order difference sequence of daily returns is a stationary time series and can be modeled.

Table 2 Descriptive statistics of daily returns

Observations	Mean	Maximum	Minimum	S.D.	Skewness	Kurtosis	JB
973	0.00031	0.029697	-0.040045	0.0087	-0.29304	4．75516	138.8176

From Table 2, it can be seen that the average closing price return of the new energy vehicle sector is close to 0 and greater than 0, indicating an overall upward trend in stock prices; The standard deviation is close to 0, relatively stable; From the skewness perspective, the skewness of stock price daily returns is less than 0, showing a left leaning trend, indicating that there are more times when the daily returns are below the average; From the perspective of kurtosis, the kurtosis of daily stock price returns is significantly greater than 3, indicating a greater likelihood of extreme values in daily stock price returns. On the whole, the daily return rate of the energy vehicle sector shows the characteristics of "peak and fat tail", and the JB test value is 138.8176, which is far more than 6, so this time series refuses to obey the original hypothesis of Normal distribution

(2) Autocorrelation test

Table 3 Autocorrelation test of daily return rate

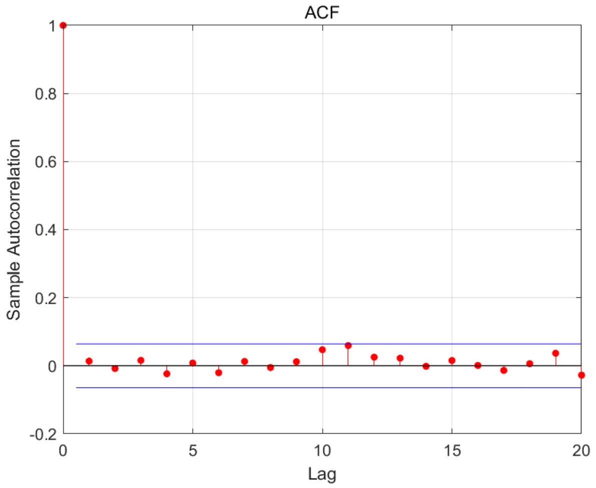

Table 4 Partial correlation test of daily returns

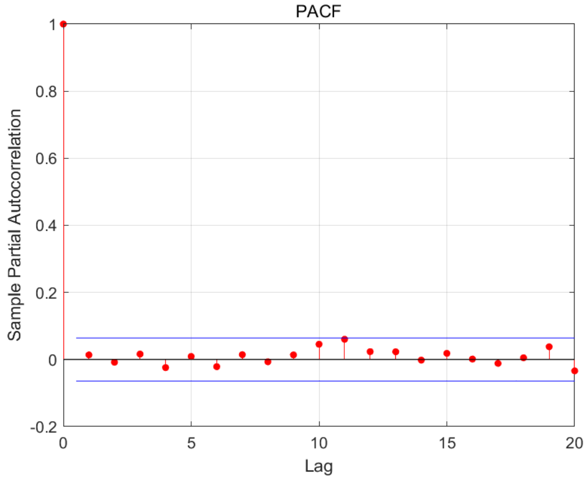

Table 3 and 4 show the autocorrelation and partial autocorrelation calculation results of the daily return series of the new energy vehicle sector. It can be seen from the figure that the lag order of the autocorrelation coefficient is 11, and the order of the partial autocorrelation coefficient is 11. Accordingly, the final prediction error FPE value of the established ARMA (11,11) model is 0.0005012, and the Mean squared error MSE value is 0.00003165.

(3) Diagnostic testing

According to the ARMA (11,11) model of the daily return rate of the new energy vehicle market, white noise tests are conducted on their residual sequences. If the residual sequence is not a white noise sequence, it means that there is still some valuable information in it, and the model needs further improvement. This article first uses the "reid" function to generate a residual sequence for this model, then uses the "lbqtest" function to test the autocorrelation of the residual sequence, and uses the "archtest" function to test the ARCH effect of the residual sequence. Based on the program running results, it is determined whether there is valuable information waiting for mining in the stock price daily return residual sequence.

The output of the sequence autocorrelation LBQ test for the ARMA (11,11) model is 1, and the result of the ARCH effect test is 0, indicating that there is no ARCH effect in the residual sequence. Furthermore, ARCH effect tests with 10, 15, and 20 lag orders were performed on the corresponding model residual sequences of the two stages, and the output results are 0,1,1, indicating that there is a high-order ARCH effect, also known as the GARCH effect, in the daily return of the energy vehicle sector stock price, Therefore, we are considering further establishing the GARCH model.

4.2. GARCH modeling and simulation

The GARCH model originates from the extension of the constraints of the ARCH model. The variance equation of the GARCH model adds a time delay structure to the ARCH model's variance equation, thereby solving the problem of insufficient parameter estimation efficiency in high-order ARCH models. It has a wider application in empirical research. For the daily return series of stock prices in this sector, GARCH (1,1), GARCH (1,2), and GARCH (2,1) models are established respectively. The results are as follows:

Table 5 GARCH(1,1)

	Value	**standardError**	**TStatistic**	**PValue**
Constant	2.8404e-06	1.3319e-06	2.1326	0.03296
GARCH{1}	0.88679	0.01918	46.235	0
ARCH{1}	0.077373	0.012998	5.9527	2.6373e-09

Table 6 GARCH(1, 2)

	Value	standardError	TStatistic	PValue
Constant	4.1746e-06	1.7569e-06	2.3761	0.017496
GARCH{1}	0.84926	0.027408	30.986	8.2671e-211
ARCH{1}	0.018835	0.025255	0.74578	0.4558
ARCH{2}	0.078278	0.027351	2.862	0.0042096

Table 7 GARCH(2, 1)

	Value	standardError	TStatistic	PValue
Constant	2.8573e-06	1.736e-06	1.6459	0.099791
GARCH{1}	0.88623	0.42026	2.1087	0.034967
GARCH{1}	2e-12	0.38562	5.1864e-12	1
ARCH{2}	0.077737	0.028654	2.7129	0.0066695

Table 8 Aic, Sc, Hq Criterion

(p, q, r)	AIC	SC	HQ
(1, 1, 0)	-6.756182	-6.721014*	-6.742797*
(2, 1, 0)	-6.757838*	-6.717646	-6.742540
(1, 2, 0)	-6.755962	-6.715770	-6.740664

The maximum lag order q of the GARCH term and the maximum lag order p of the ARCH term are included.

According to the three information criteria of AIC, SC, and HQ, GARCH (1,1) was found to have the best fitting effect. Therefore, GARCH (1,1) was established, with a GARCH of 0.88679, indicating that the current variance still has an impact on the next period's variance, with nearly 90% of the shocks still present in the next period; The sum of GARCH and ARCH terms is 0.964163. Less than 1 satisfies the parameter constraint and is very close to 1, indicating that the impact on the conditional variance is persistent and the attenuation of volatility is slow. Once large fluctuations occur, it is difficult to eliminate them in the short term, and the impact plays an important role in all future predictions.

4.3. Testing the stationarity of daily return series

Next, we use the "simulate" function to conduct Monte Carlo simulation on the daily stock price return series of the "mainland low-carbon" plate, and explore the volatility of the daily stock price return series from the model. The number of Monte Carlo simulation paths is 500, and the number of phases is 100. The simulation results are shown in the figure below.

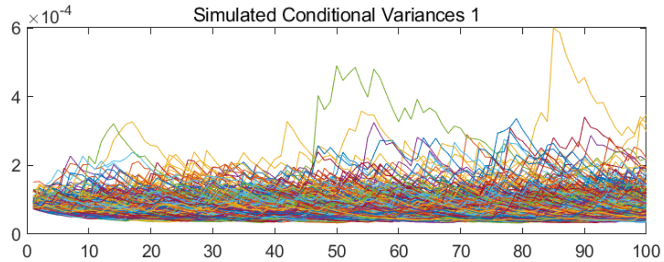

Figure 1 Monte Carlo result 1

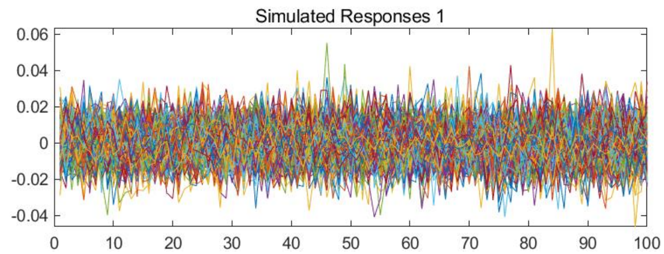

Figure 2 Monte Carlo result 2

From Figures 1 and 2, it can be seen that the volatility of variance is relatively high. As the number of periods increases, the volatility increases. The sample simulation results are similar, indicating that relevant new energy vehicle companies have certain income fluctuations and require certain risk prevention.

The following is the Monte Carlo prediction of 30 periods based on 100 periods, which is run with the forecast function, and the results are shown in Figure 3.

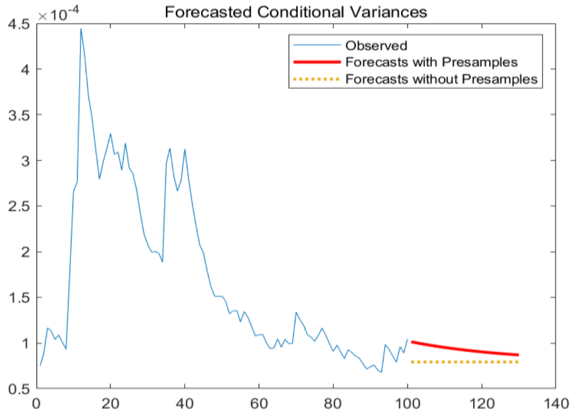

Figure 3 Forecasted Conditional Variances

The red line represents sample based prediction, while the dashed line represents sample free prediction. It can be seen that the stock price will slightly decrease in the next 30 periods and the volatility will tend to stabilize.

4.4. The Impact of Policy Uncertainty and Economic Uncertainty

This article uses the daily closing price returns (974 data) of the "National Securities New Energy Vehicle Index" sector from September 1, 2017 to August 31, 2021, as well as policy uncertainty (EPU) and manufacturing purchasing managers' index (PMI) indicators from September 1, 2017 to August 31, 2021. The PMI indicator represents the development status of the industrial economy and serves as an economic uncertainty indicator to construct the GARCH-MIDAS model, Study the impact of low-frequency data of policy uncertainty and economic uncertainty on the high-frequency data of daily returns of the new energy vehicle sector. In order to calculate the GARCH-MIDAS model, this article multiplies the daily closing price logarithmic return by 100.

The following two figures show the trend of EPU and PMI:

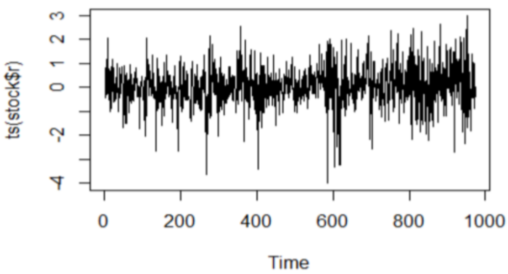

Figure 4 R

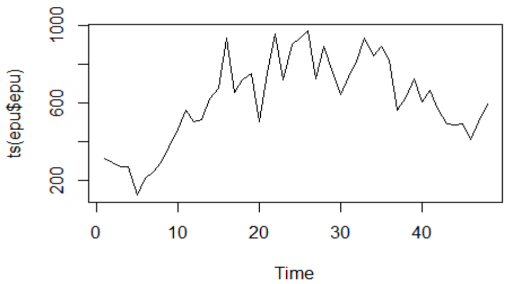

Figure 5 EPU

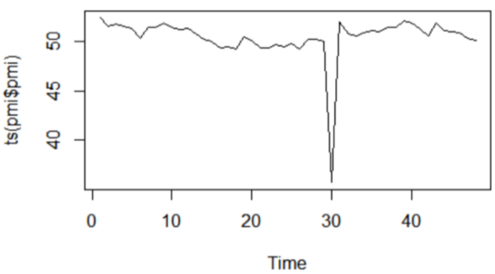

Figure 6 PMI

From the two figures, we can see that the stock price is generally stable, and there is Homoscedasticity and heteroscedasticity in some parts, which is consistent with the previous test results. The EPU has experienced significant fluctuations in recent years, possibly due to the impact of the pandemic in the past year, as well as supply side reforms and countercyclical conditions, which have led to policy instability. The change trend of the PMI index in recent years deserves attention. In the first half of 2020, the PMI index plummeted due to the impact of the epidemic on industry. In response to the downward pressure on the economy during the epidemic, the central bank has comprehensively adopted the methods of reducing reserve ratio, MLF interest rate and LPR, and reverse repo interest rate to support the real economy to overcome the epidemic since the beginning of the year. The significant acceleration of M2, loans, and social finance indicates that the real economy has indeed obtained low-cost liquidity, and enterprises have received "blood transfusion" during the epidemic period. Loose monetary policy has played a significant supporting role in stabilizing and recovering the economy. Therefore, from the second half of 2020 to August 2012, the economy gradually recovered, and the PMI index rebounded.

According to the GARCH-MIDAS model, X1 is the EPU and X2 is the PMI. This article selects one year as the lag period, so K=12. The parameter results are shown in the table below:

Table 9 Empirical Result

	RV	$RV + EPU$	$RV + PMI$
μ	0.07411005**	0.71454609**	7.556663e-02**
α	0.08468778***	0.074655005**	8.651727e-02**
β	0.87516700***	0.913812131***	8.768478e-01***
γ		-0.039748670	-2.672390e-04
$\theta 1$	-437.15027887	36.3222182095**	-1.237893e+02
$\theta 2$		-0.002821698***	1.328781e-01
$\omega 12$	3.87155304***	1.000006215***	7.157697e+00***
$\omega 22$		83．812903793***	1.587411e+00
m	13.03777428	0.714202121	-3.078333e+00
LLF	-935.0729	-925.3708	-936.8347
BIC	1909.688	1910.054	1932.982

Note: RV represents the benchmark model that only includes realized volatility; RV+X is the GARCH-MIDAS-X model with indicators of economic uncertainty and policy uncertainty, LLF is the maximum Likelihood function value, and BIC is the information criterion; The robust standard deviations of the coefficients in parentheses: *, * *, * * * respectively represent significant within the 10%, 5%, and 1% levels.

In the estimation of the new energy vehicle sector in Table 5, the parameters of the GARCH section(μ,α,β). It is statistically significant, indicating that the short-term volatility of the new energy vehicle sector exhibits a strong volatility aggregation effect. θ_ 1 and θ_ 2. Respectively reflect the long-term impact of realized volatility, economic uncertainty (including economic policy uncertainty EPU and macroeconomic uncertainty represented by the PMI index) on volatility, RV and RV+PMI models θ_ 1 is negative, but in the model of RV+EPU θ_ 1 is positive, indicating that when the RV changes in the current month, the long-term component impact on the volatility of the next month is inconsistent. When the volatility achieved in the current month is increased separately or when the volatility and macroeconomic uncertainty are both increased in the current month, it will reduce the long-term component of the volatility of the new energy vehicle sector in the next month. However, when the realized volatility and economic policy uncertainty indicators in the current month are increased simultaneously, The long-term component that will increase the volatility of new energy sector vehicles next month is significant. EPU's θ_ The significant negative sign of 2 indicates that when economic policy uncertainty increases, it will reduce the long-term volatility component of the new energy vehicle sector stock. PMI's θ_ The 2 symbol is positive but not significant, indicating that when macroeconomic uncertainty increases, it may increase the long-term volatility component of the new energy vehicle sector.

The GARCH-MIDAS mixed frequency model with uncertainty variables can observe differences in volatility components, which is different from the GARCH model. It only focuses on the parameters of the GARCH model and cannot understand the impact of realized volatility and economic uncertainty factors on long-term stock market volatility within the month.

It can be noted that the results of the three measurements of RV, RV+EPU, RV+PMI in the table α,β The sum of the two is close to 0.90, and under the standard GARCH model, the sum of the two is close to 1. Similar phenomena have also been observed in Engle et al. [8]'s research literature on stock markets in other countries and regions.

According to the BIC criteria, it was found that there was no clear improvement in the model incorporating economic policy uncertainty indicators compared to the benchmark model RV, and the improvement in the manufacturing purchasing managers' index (PMI) incorporating macroeconomic uncertainty indicators was not significant compared to the benchmark model RV.

The following figure shows the weight chart of RV, EPU, and PMI indicators in the new energy vehicle sector over the past 12 months. The horizontal axis represents the order of lag, and the vertical axis represents the weight. During the 12 month observation period, the decay rate of EPU was the fastest, only having an impact on the long-term trend of the new energy vehicle sector in the first two months. RV had a fixed impact weight on the long-term trend of the new energy vehicle sector in the first 10 months or so, and the impact weight rapidly decreased from November to December. The PMI index's impact weight on the new energy vehicle sector slowly decreased in mid December, compared to the first two indicators, The impact weight of this indicator on the observation of the new energy vehicle sector in a 12 month lag period is relatively uniform, showing a slow downward trend. The macroeconomic indicators of the manufacturing industry have a relatively long impact on the new energy vehicle sector, which takes about a year to dissipate. At the same time, it also indicates that the impact of economic operation on the new energy vehicle sector has a relatively long duration, but the impact between the entire lag period is uneven, with the lag period in December rapidly fading in the last two months. The impact of economic policy uncertainty on the volatility of the new energy vehicle sector has a relatively short duration and can quickly dissipate within two months. That is to say, the impact of economic policy uncertainty on the stock price of the sector presents a short-term effect, and the impact from policies is digested within two months.

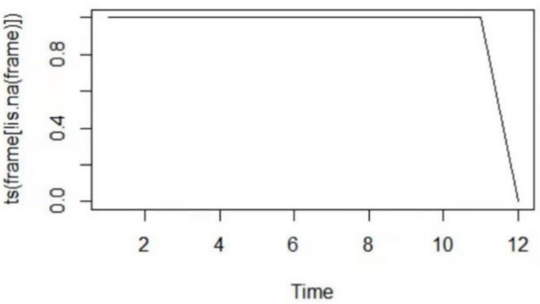

Figure 7 Beta Function Weight Graph of RV

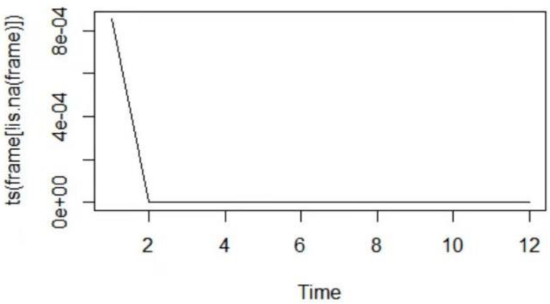

Figure 8 Beta Function Weight Graph for EPU

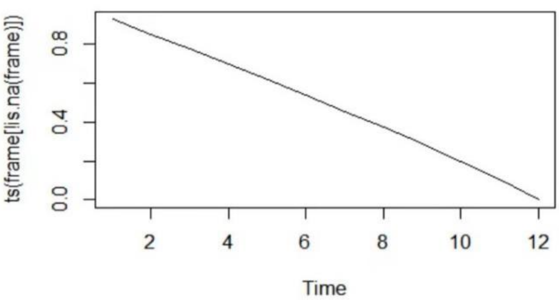

Figure 9 Beta Function Weight Graph for EPU

5. Summary

This article revolves around the issue of how the uncertainty of the Ministry of Economic Affairs affects stock volatility in the new energy vehicle market. Analyze the impact of macroeconomic and macroeconomic policy uncertainty on stock price volatility in the new energy vehicle market by using the Mixed Frequency Volatility Model (GARCH-MIDAS). The results indicate that economic policy uncertainty has a significant negative impact on the volatility of the new energy vehicle market. When economic policy uncertainty increases, market volatility will decrease. The mixed frequency model with macroeconomic uncertainty indicators does not significantly improve the fitting effect of the model, and has a small contribution to market volatility. The long-term impact of macroeconomic uncertainty on the volatility of the new energy vehicle market is transmitted from the manufacturing purchasing managers' index. The PMI index's impact on the new energy vehicle sector has slowly decreased over the past 12 months, and the impact of macroeconomic indicators on the new energy vehicle sector is relatively long, taking about a year to dissipate, The fluctuation of economic policy uncertainty on the new energy vehicle market is transmitted through the EPU index, and the impact of economic policy uncertainty presents a short-term effect. Policy shocks are absorbed within 2 months and will not have a long-term impact on the stock market. Among all economic uncertainty factors, economic operation has the most significant impact on long-term volatility. Overall, macroeconomic uncertainty does not have a significant impact on the volatility of the new energy vehicle market, and its contribution is limited.

This article establishes the GARCH-MIDAS model from the perspectives of stock price (daily data) and macro (monthly data), which helps to observe stock market volatility in multiple dimensions. This article argues that although economic uncertainty may affect the long-term trend of stock price volatility in the new energy vehicle market, its impact is not significant and its contribution is limited.

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